

Study on Support Vector Machine for Image Reconstruction Algorithm of Electrical Capacitance Tomography

HAN Yuhui¹, HUANG Jingluo², SHEN Lili³

¹Henan Engineering Centre of Automation, ²Henan Academy of Sciences, ³Henan Polytechnic

Abstract—Support vector machine (SVM) is based on the special small samples theory with strong generalization ability, and is selected as an optimal theory for small samples classify problem. Electrical capacitance tomography (ECT) is a typical small samples and nonlinear mapping problem. In this paper the ECT image reconstruction algorithm based on SVM is proposed and a novel training method is proposed to improve the efficiency of SVM classifier by selecting active penalty parameters. Programming software based on Matlab6.5 and VC6.0, the simulation and experiment results indicates this algorithm has stronger space resolution and generalization ability, overall performance of the algorithm is better than some classic reconstruction algorithm such as LBP, etc. However, the algorithm requires the higher quality of training samples, otherwise less real-time, loss of application value.

Keywords—support vector machine; electrical capacitance tomography; image reconstruction; space resolution; generalization ability

Identification of Multiphase Flow widely in petroleum, chemical industry, river training and other areas of national product, as the complexity of multiphase fluid, random much, it is difficult using traditional detection techniques to accurately measure. Electrical Capacitance Tomography (ECT) technology is the use of multiphase medium tending to have a different dielectric constant, through the array of electrode capacitance changes, reflecting the multiphase medium pipeline distribution to extract the phase of each phase medium concentration, relative size, flow patterns and other characteristic parameters. The technology can be used to detect two-phase / multiphase flow processes, real-time display phase distribution images of multiphase fluid in the pipeline to achieve phase concentration, flow patterns and other characteristic parameters, is a measurement of high speed, non-invasive, low cost, applicable to a wide range of a new generation non-destructive functional imaging techniques [1].

Electrical capacitance tomography system includes capacitance sensor, data acquisition and signal processing unit, image reconstruction and analysis display three functional modules. As the "soft field" feature of system sensitive field,

less independent capacitance measurements and other factors, makes the image reconstruction algorithm for the overall performance of the system plays a decisive role. As the current practical image reconstruction method are mostly qualitative algorithms (such as linear back projection algorithm), at the expense of accuracy to improve the real-time imaging, making the reliability of the extracted characteristic parameters less, and some high precision real-time imaging algorithm more poor, and no practical value.

For less of independent capacitance value for the system, this paper design an image reconstruction algorithm for electrical capacitance tomography based on support vector machine (SVM) from statistical learning theory [2].

I. SVM ALGORITHM DESIGN

Support vector machine by Vapnik first proposed (Vapnik, 1995), is the structural risk minimization method to achieve approximate. It integrates the largest interval of hyper-plane, Mercer core; convex quadratic planning, sparse solutions and slack variable technologies can be used for pattern recognition and nonlinear regression, which has become a standard tool for machine learning [3]. The 12-electrode capacitance sensor, for example, the system has 66 independent capacitance values, then an output unit for the support vector machines architecture shown in Figure 1, the number m_0 of the input layer units are equal to 66, the number m_1 of hidden layer units are decided by support vector number in the system. The core of support vector machines makes the non-linear input space into linearly separable feature space through the inner core function $K(x, x_i)$ [4].

Make $\{\varphi_j(\vec{x})\}_{j=1}^{m_1}$ express a collection of non-linear

transformation from the input space to feature space, in which $\vec{x}$ is the input space vector.

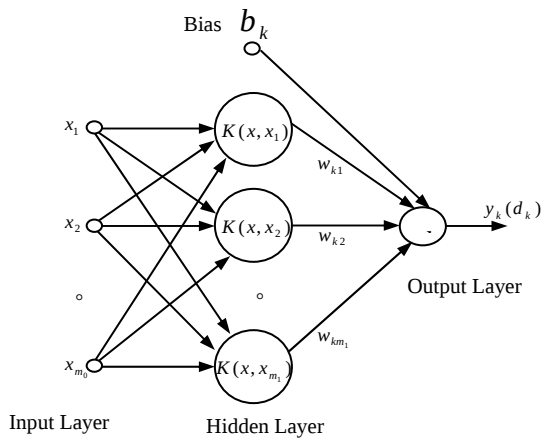


Fig.1 SVM architecture of output unit

$y_k = d_k = +1$ Indicate existence of high dielectric constant material in the output unit.

$y_k = d_k = -1$ Indicate existence of low dielectric constant material in the output unit.

Where y_k is output value of the output unit, d_k is target value of the output unit.

So the inner product kernel function as

$$K(\vec{x}, \vec{x}_i) = \langle \vec{\varphi}(\vec{x}) \cdot \vec{\varphi}(\vec{x}_i) \rangle = \sum_{j=1}^m \varphi_j(\vec{x}) \varphi_j(\vec{x}_i) \quad (1)$$

$$i = 1, 2, \dots, N$$

N for training sample size, There is the number $(\vec{x}_i, \vec{d}_i)_{i=1}^N$ of training samples.

Selecting the radial basis function for the inner product kernel function:

$$K(\vec{x}_i, \vec{x}_j) = \exp\left(-\frac{1}{2\sigma^2} \|\vec{x}_i - \vec{x}_j\|^2\right) \quad (2)$$

Supposing the k output unit:

A given training sample $(\vec{x}_i, \vec{d}_i)_{i=1}^N$, Using convex quadratic planning algorithm for maximizing the objective function.

$$\text{Max}Q(\alpha) = \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j d_i d_j K(\vec{x}_i, \vec{x}_j) \quad (3)$$

$$\text{Constraints: } \textcircled{1} \sum_{i=1}^N \alpha_i d_i = 0$$

$$\textcircled{2} \quad 0 \leq \alpha_i \leq C \quad i = 1, 2, \dots, N$$

And to meet the constraints of the Lagrange multiplier α_i , then its corresponding training sample $\{\vec{x}_i\}$ is a support vector. So that does not meet the constraints of the Lagrange multiplier set 0. C in the constraints $\textcircled{2}$ for the penalty parameter[5].

Corresponding to the optimal weight vector is

$$\vec{w}_{ok} = \sum_{i=1}^N \alpha_{oi} d_i \vec{\varphi}(\vec{x}_i) \quad (4)$$

The output of the number k unit is as follows:

$$y_k = \sum_{i=1}^N \alpha_{oi} d_i \vec{K}(\vec{x}, \vec{x}_i) + b_k \quad (5)$$

Where b_k takes the b value arithmetic mean value of the support vector collection substitution equation (5).

II. IMAGE RECONSTRUCTION SIMULATION

By the two dimensional finite element method analyzing system sensitive field, adopts triangle meshing and linear interpolation to seeking sensitive field electric potential distribution and examination pole plate capacitance [6]. If the sensitive area, the pipeline wall and the pipeline outer wall to the shielding layer region's meshing layer respectively is 4 and 3 and 3. Programming software based on Matlab6.5 and VC6.0, meshing map shown in Figure 2.

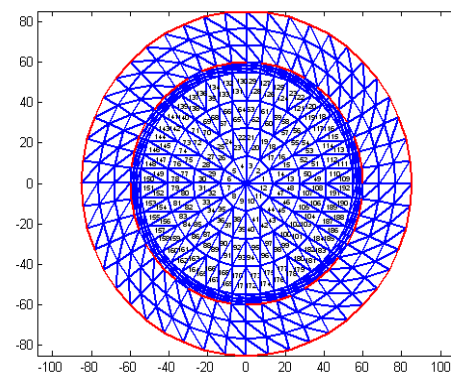


Fig.2 System meshing map and sample numbers

Simulation Capacitance value using equation (6) for normalized [7].

$$\tilde{C}_{i,j} = \frac{C_{i,j}^m - C_{i,j}^e}{C_{i,j}^f - C_{i,j}^e} \quad (6)$$

If imaging medium is A,B and $\varepsilon_A > \varepsilon_B$, among: $C_{i,j}^f, C_{i,j}^e$ is respectively the capacitance value when the tube filled with

$$C_+ = \frac{L_-}{L_+ + L_-} C, \quad C_- = \frac{L_+}{L_+ + L_-} C \quad (7)$$

Where, L_+ and L_- is the number of positive class and negative class point sets. C_+ and C_- are penalty parameters of positive class and negative class point sets. Then the equation (3) change as :

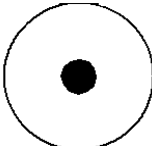
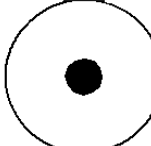
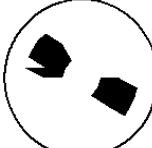
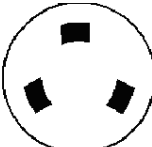
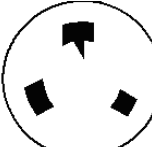
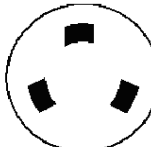
No.	Set Images	Simulation images of the static C	Simulation images of the dynamic C
1			
2			
3			

Fig.3 SVM image reconstruction comparison chart based on static and dynamic penalty parameter.

A-phase and B-phase medium, $C_{i,j}^m$ is the capacitance value when the tube filled with A, B for the two-phase medium.

Based on 700 groups of training samples, select the equation (3) constraints ② training network of the $C=8$ to generate support vector set. Static C reconstructed image in figure 3 for the test samples (as distinct from the training sample) is the simulation images based on the support vector set through static threshold filtering. By the diagram shows, Space resolution, generalization ability of the algorithm is better than the linear back-projection, radial basis function neural network image reconstruction algorithm. But its space resolution error is still large, poor usability.

As great differences of the numbers between positive class and negative class point sets. But the penalty parameter C in the equation (3) is static, this means that the number of certain types is more, then the penalty will be heavier, but we hope the same degree of punishment to positive class and negative class point sets, so structure the different penalty parameters:

$$MaxQ(\alpha) = \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j d_i d_j K(\vec{x}_i, \vec{x}_j) \quad (8)$$

$$\text{Constraints: } ① \sum_{i=1}^N \alpha_i d_i = 0$$

$$② \quad 0 \leq \alpha_i \leq C_+, \quad d_i = 1$$

$$0 \leq \alpha_i \leq C_-, \quad d_i = -1$$

$$i = 1, 2, \dots, N$$

Based on the same 700 groups training samples, select the equation (8) constraints ② training network of the $C=8$ to generate support vector set based on the equation (7). Dynamic C reconstructed image in figure 3 for the test samples (as distinct from the training sample) is the comparison chart based on the support vector set through static threshold filtering. From the diagram shows, the space resolution error, generalization ability of the algorithm is better than image reconstruction algorithm based on static C , strong usability [8][9].

III.EXPERIMENT AND ANALYSIS

Algorithm performance testing mainly study imaging experiments of the different numbers, different sizes and different locations of static objects, a single object, two objects, multiple objects, imaging experiments were selected to a diameter of 10mm and 20mm and 30mm of the Plexiglas rods.

capacity, generalization ability, overall performance of the algorithm is better than LBP, etc. However, the algorithm requires the higher quality of training samples, otherwise less real-time, loss of application value.

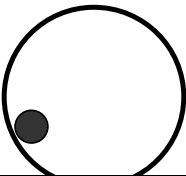
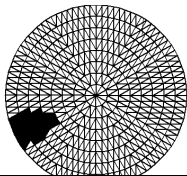
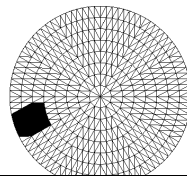
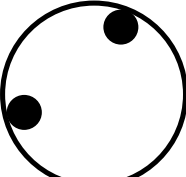
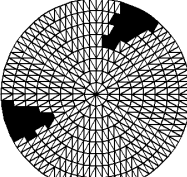
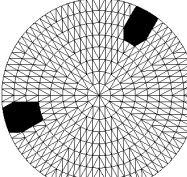
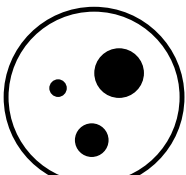
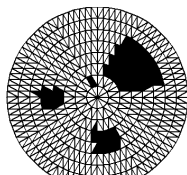
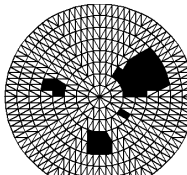
No.	Type	Distribution map of the physical model	Reconstruction images of the static C	Reconstruction images of the dynamic C
1	1 20mm			
2	2 20mm			
3	1 30mm 1 20mm 1 10mm			

Fig.4 Imaging results test of plexiglass rods

The following conclusions from the experimental results figure 4:

- ① The small diameter objects reconstructed images results rather vague, large diameter objects better reconstructed images;
- ② The closer to the center, the reconstruction image more blurred, the closer to the edge, the better the reconstructed image;
- ③ Images from SVM algorithm based on dynamic C than based on static C clearer, more precise.

IV.CONCLUSIONS

Image reconstruction problem of electrical capacitance tomography can be reduced to a class of linear inseparable problems, this paper based on dynamic penalty parameter, and convex quadratic planning in support vector machine, programming software based on Matlab6.5 and VC6.0, the image reconstruction of the simulation and experimental results show that the algorithm has stronger space resolution

REFERENCES

- [1] Wang Huaxiang, Yang Wuqiang. The Latest Development of Capacitance Process Tomography System. Chinese Journal of Scientific Instrument, 2000,21(1):4-7,11
- [2] Nello Cristianini, John Shawe-Taylor. An Introduction to Support Vector Machines. Beijing: Electronic Industry Press, 2004
- [3] Deng Naiyang, Tian Yingjie. The new method in Data Mining -support vector machine. Beijing: Science Press, 2004
- [4] Scholkopf B, Burgs C J C, Smola A J. Advances in Kernel Methods Support Vector Learning. MIT Press,1999
- [5] Boser B E, Guyon I M, Vapnik V.A training algorithm for optimal margin classifiers. Proceedings of the 5th annual ACM Workshop on Computational Learning Theory , Pittsburgh, PA, July ACM Press,1992:144-152
- [6] Wang Huaxiang, Zhang Lifeng, Zhu Xueming. Optimum Design of Array Electrode for ECT System. Journal of Tianjin University, 2003,36(3):307-310
- [7] Yang Lijian, Yan Hua. Normalisation Approach for Capacitance Tomography Measurement Data. Chinese Journal of Scientific Instrument, 2002,23(3): 229-231
- [8] Zhang Lifeng, Wang Huaxiang. Identification of two-phase flow regime based on support vector machine and electrical capacitance tomography technique. Chinese Journal of Scientific Instrument, 2009,(04): 812-816
- [9] Liu Haoyang, Chen Deyun, Li Mouzun. Image Reconstruction Algorithms of Electrical Capacitance Tomography Based on Support Vector Machine. Journal of Harbin University of Science and Technology,2006,(04):1-4.